# Myocardial Ischemia Detection with ECG Analysis, Using Wavelet Transform and Support Vector Machines

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*Abstract*— **In this paper, we propose a novel method for the detection of myocardial ischemic events from electrocardiogram (ECG) signal, using the Discrete Wavelet Transform (DWT) technique and Support Vector Machines (SVM). The ST-T Segment is obtained based on the detection of R peak location based on the well-known Pan-Tompkins method. Then ratio of energy in the DWT approximation coefficients rather than detail coefficients calculated as the features. SVM is used to build classifiers for ischemic and normal ECG signals. The proposed method achieved correct rate of 98.2%, sensitivity of 98.43% and specificity of 99.45%.**

***Keywords- ECG; Myocardial Ischemia; Wavelet transform; SVM.***

## I. INTRODUCTION

Myocardial Ischemia is one of the most common causes of death in the world and early diagnosis and treatment of it has a critical importance. Ischemia is caused by a blockage in the arteries leading to the heart [1]. This type of blockage deprives the cardiac tissue of necessary oxygen. Without oxygen, the cardiac tissue begins to die leading to a myocardial infraction or heart attack. Decrease cardiac oxygenation, effect ventricular repolarization. The damaged cardiac tissue does not depolarize as quickly as the healthy tissue. This causes some of the depolarizing wave to appear during the normally isoelectric ST segment (the time between the S wave and the T wave). If the damage is severe enough, it may even affect the T wave. By using features derived from the modified ST segment and T wave it may be possible to determine if a patient is experiencing ischemia [2,3]. As the ECG analysis is the most accurate, safe and none invasive method in myocardial ischemia detection, several works has been reported in this area. Badilini et. al [4] used frequency domain analysis. They found that ischemic episodes have a lower frequencies term than normal episodes. Stamkopoulos et.al [5] used MLPNN for detection of Ischemia episodes. P.Ranjith et.al [6] used quadratic spline wavelet transform for extraction features of ECG signal and [7] used DCT coefficients and MLPNN for classifying ischemic episodes.

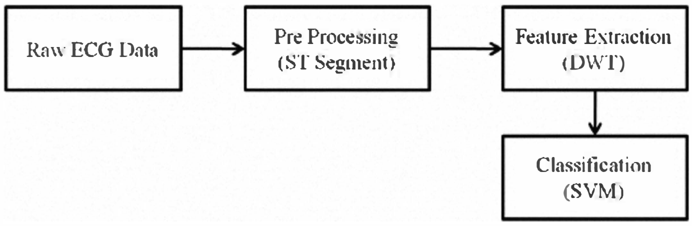


Figure 1: block diagram of the system

In this paper we used ratio of energy in the approximation coefficients of ECG signal as the features. Then we used SVM classifier for classifying normal and ischemic episodes. Fig.1 shows ECG signal analysis flowchart. In the following sections of this paper, we present the method that are used for ST-T segment detection. Third section describes feature extraction procedure. The classification techniques are discussed in section 4. We argue analysis results in the fifth section.

## II. ST-T SEGMENT DETECTION

Fig. 2 shows a complete ECG wave and ST-T segment. In order to detect ST-T segment, first we found peak of the R location. There are several methods [8] have been proposed for detecting QRS complex. We used the well-known Pan&Tompkins method [9] for detection of QRS complex. This method is based on analysis of the slope, amplitude and width of QRS complexes. The algorithm includes a series of filters and methods that perform lowpass, highpass, derivative, squaring, integration, adaptive thresholding and search procedures. Fig. 3 illustrates the steps of the algorithm in the schematic form. In the first step the algorithm passes the signal through a low pass and a high pass filter in order to reduce the influence of the muscle noise, the power line interference, the baseline wander and the T-wave interference. After filtering, the signal is differentiated to provide the QRS slope information using the following formula:

$$y(n) = \frac{1}{8}[2x(n) + x(n-1) - x(n-3) - 2x(n-4)] \quad (1)$$

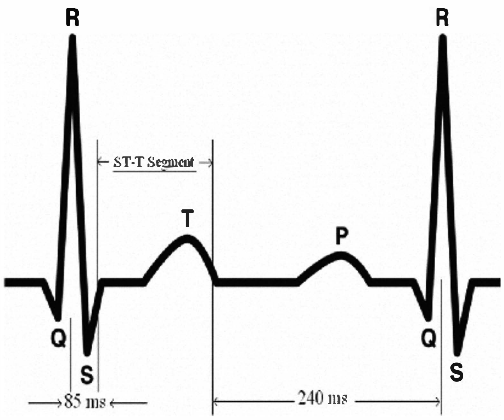


Figure 2: ST segment between tow R peaks

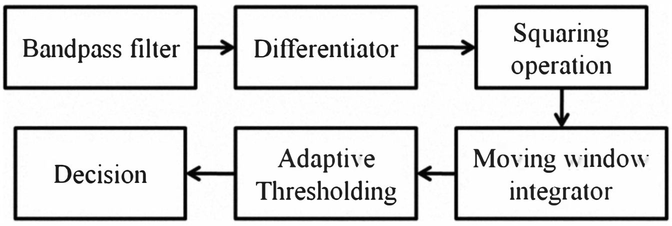


Figure 3: Block diagram of Pan Tompkins algorithm

Then the signal is squared point by point making all data point positive and emphasizing the higher frequencies. After squaring, the algorithm performs sliding window integration in order to obtain waveform feature information.

A temporal location of the QRS is marked from the rising edge of the integrated waveform. In the last step two thresholds are adjusted. The higher of the two thresholds identifies peaks of the signal. The lower threshold is used when no peak has been detected by the higher threshold in a certain time interval. In this case the algorithm has to search back in time for a lost peak. When a new peak is identified (as a local maximum – change of direction within a predefined time interval) then this peak is classified as a signal peak if it exceeds the high threshold (or the low threshold if we search back in time for a lost peak) or as a noise peak otherwise. In order to detect a QRS complex the integration waveform and the filtered signals are investigated and different values for the above thresholds are used. To be identified as a QRS complex, a peak must be recognized as a QRS in both integration and filtered waveform.

## III. FEATURE EXTRACTION

The purpose of the feature extraction process is to select and retain relevant information from original signals .The discrete wavelet transform was first applied to decompose the original ECG signals into frequency bands. One of the advantages of the wavelet transform is that it is able to decompose signals at various resolutions, which allows accurate feature extraction from non-stationary signals like ECG [10].The features of signals, such as ratio of energy in the approximation coefficients, were then extracted as features vector.

### *A.* Wavelet transform

Fourier transform (FT) is the representation of a signal as a sum of sinusoids and is only localized in frequency. But the wavelet transform is localized in both time and frequency domains. Wavelet Transform is used to find the instant at which the abrupt change has taken place in the frequency domain at a particular instant of time. After performing WT, a set of wavelet coefficients will be produced and each of these coefficients represents the power of that specific component of the signal in a frequency sub-band at a specific time. Fig.4 shows the diagram of wavelet decomposition levels and approximation and detail coefficients. The wavelets are small waves having finite period of time (compactly supported, does not extend from negative to positive infinity). Hence, the WT is a more useful technique to be used for ECG signal analysis as compared to Fourier transform.

### *B.* Feature Vectors

In feature extraction process the energy of coefficients was obtained from a decomposed signal at each level. Energy contained in wavelet coefficient at each scale given by:

$$E_m = \sum_n \left| W_{m,n} \right|^2 \tag{2}$$

were $W_{m,n}$ is the n'th coefficient at level m. In each level, the energy of approximation in that level and details in all levels calculated and then percentage of energy in approximation rather than energy of details obtained as the feature. For example in third level (like fig.4) the feature obtains as follow:

$$F_{E3} = \frac{E_{AAA3}}{E_{DAA3} + E_{DA2} + E_{D1}} \times 100 \tag{3}$$

That $E_{AAA3}$ denotes energy of approximation in third level decomposition and $E_{DAA3}, E_{DA2}$ and $E_{D1}$ represent energy of details in third, second and once level respectively.

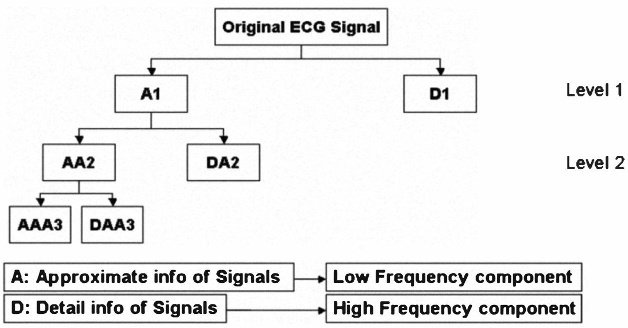


Figure 4: Diagram of decomposition levels in Wavelet transform

## IV. CLASSIFICATION

The third stage is the feature classification. The features extracted in the second stage were classified using a technique called support vector machines (SVM). SVM is a new classification method for both linear and nonlinear data. It uses a nonlinear mapping to transform the original training data into a higher dimension. With the new dimension, it searches for the linear optimal separating hyper plane [11]. By plotting the feature vectors of different types of known signals, groups of vector points, known as clusters can be obtained. Each cluster represents a different class; for ECG signals, the classes could be normal ECG or ischemic ECG. SVM finds this hyper plane using support vectors ("essential" training tuples) and margins (defined by the support vectors) (Fig. 5). With an appropriate nonlinear mapping to a sufficiently high dimension, data from two classes can always be separated by a hyper plane.

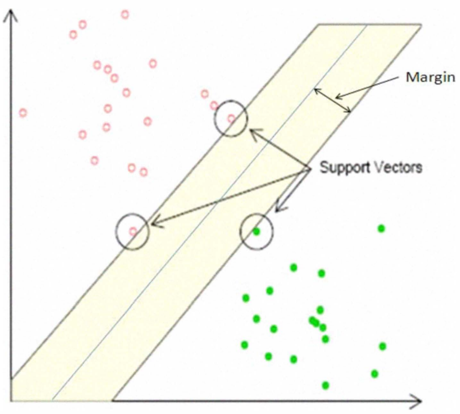


Figure 5: Margin and support vector in SVM

## V. RESULTS AND DISCUSSIONS

To demonstrate the effectiveness of this technique, the digitized ECG data were taken from the European *ST–T* database. The European *ST–T* change database [MIT] consists of the recordings of 90 double channel 2-h ECG signals with a sampling rate of 250 Hz, which contain *ST–T* complex episodes annotated on an individual lead basis by cardiologists. The amplitude scale is 5 uV/point. We used dataset contain of 16 patients with 8 normal and 8 ischemic ECG signal for evaluation proposed method.

The performance evaluation method for ischemic signal detection algorithm consist of calculating 3 indices, with are; correct rate, sensitivity and specificity that can be shown in table 1 and table 2 and described as follow respectively:

- Correct rate:

$$CR = \frac{2N_{T_p}}{N_N + N_I} * 100\%$$

Where $N_{T_p}$ the number of true positive and $N_N$ is the cardinality of normal ECG and $N_I$ is the cardinality of ischemic ECG, denotes ratio of correct detection normalized by both normal and ischemic data.

- Sensitivity:

$$Se = \frac{N_{T_p}}{N_{T_p} + N_{F_N}} * 100\%$$

Where $N_{F_N}$ is the number of false negative.

- Specificity:

$$Sp = \frac{N_{F_p}}{N_{T_p} + N_{F_N}} * 100\%$$

Where $N_{F_p}$ is the number of false positive.

We applied proposed method in 5 and 7 beats and in 5, 7, 9 and 11 wavelet decompose levels. Result shows that 7 beat led better result than 5 beat. Using 11 level decompositions for calculating features led best results comparing another level decomposition. Using wavelet energy and SVM classifier we obtained 99.4% of correct rate, 98.56% of sensitivity and 99.76% of specificity.

TABLE I. RESULTS USING **5** BEATS OF ECG

| **Decompose level** | **Correct Rate (%)** | **Sensitivity (%)** | **Specificity (%)** |
|---|---|---|---|
| 5 | 96.78 | 97.5 | 96.25 |
| 7 | 97.5 | 95 | 100 |
| 9 | 99.2 | 98.4 | 100 |
| 11 | 100 | 100 | 100 |
| **average** | **98.1** | **98.31** | **99.13** |

TABLE II. RESULTS USING **7** BEATS OF ECG

| **Decompos level** | **Correct Rate (%)** | **Sensitivity (%)** | **Specificity (%)** |
|---|---|---|---|
| 5 | 98.2 | 95.7 | 98.1 |
| 7 | 100 | 100 | 100 |
| 9 | 100 | 100 | 100 |
| 11 | 99.4 | 98.8 | 100 |
| **average** | **99.4** | **98.56** | **99.76** |

The results obtained from each system cannot be compared directly since they were not evaluated with the same dataset. However comparing with some works like [7] that used DCT coefficients and MLP classifier and achieved 81.97% of correct rate, 77.78% of sensitivity and 86.19% of specificity, can be seen that our method led better results.

## I. CONCLUSION

In this study, we used ratio of energy in the wavelet transform approximation coefficients rather than detail coefficients as the features. Then we applied SVM classifier for separating normal and ischemic datasets. Results show that using wavelet transform and SVM can improve classification result. It was also found that ratio of energy in approximation in different levels is a feature, which is suitable for classification of ECG signals.

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